A Hybrid MCDM Model for Service Composition in Cloud Manufacturing using O-TOPSIS

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***Abstract*—The purpose of this research article was to define the current or future usage of Industry 4.0 technologies (Cloud Computing, IoT, etc.) to improve industrial manufacturing. The goal of this study is to rate the options using a hybrid CRITIC - O-TOPSIS Multi Criteria Decision Making model. The CRITIC technique is used to calculate Objective Weights. Also, when comparing the findings to TOPSIS, A thorough Systematic Literature Review comes first. Secondly, a theoretical approach to recognizing the Index System of Criteria. Third, Creating a Hybrid Model of CRITIC and O-TOPSIS for Decision Making. Lastly, Comparing and Ordering Options. The proposed technique successfully addresses the ambiguity and uncertainty of heterogeneous information while maintaining assessment data accuracy. Also, because objective weights are more grounded in reality than subjective weights, the result is more precise. CRITIC approach results reveals that Ease of Opting has the most weight and Ease of Implementation has the least weight O-TOPSIS method ranks alternatives in the following order: A4>A5>A3>A1>A2. This paper ranks alternatives based on extensive 22 criteria in Service Composition in Cloud Manufacturing using the hybrid model CRITIC - O-TOPSIS**

Keywords—Cloud manufacturing (CMFg); CRITIC method; O-TOPSIS method; service composition

I. Introduction

In tech-based manufacturing, the most cutting-edge technological techniques can be employed to govern service composition. To be more specific, the concept of Industry 4.0 emerges first in this context. The Internet of Things (IoT) and cloud manufacturing (CM) are two examples of modern digital technologies.

An optimization-based strategy is not used in the fuzzy TOPSIS technique [1]. It is suggestible to consider objectivity arising due to human intervention. In order to solve this, O-TOPSIS with Objective Weights is used in this study's ranking of the alternatives. An advanced manufacturing system selection problem with six evaluation criteria and four alternatives is given the framework [2]. It is discovered that spherical fuzzy AHP-TOPSIS works well for managing decision-making uncertainty. Making decisions in real-time scenarios requires a wide range of criteria in order to take into account several factors that could influence the process. This paper uses 22 criteria to make up for that. Most scholars believe that this phenomenon is not conducive to decision-making. Rank reversal in MCDM that may cause decision makers to ignore the differences among alternatives. Also, the rank reversal phenomenon in the TOPSIS affects the credibility of the decision results as well as the universality of its decision method [3]. The process [4] increases the effectiveness of decision-making and empowers decision-makers to choose solutions according to their significance and impact on the business. The Service Composition in Cloud Manufacturing should constantly use relevant and updated technology to avoid competition and crises in the future. This work (O-TOPSIS) attempt to extend the usability of TOPSIS.

Since rough numbers are objective in information evaluation, most other models—such as fuzzy numbers, interval numbers, the 2tL model, and the CM theory—are employed in conjunction with rough numbers to handle information aggregation in DM scenarios [5]. Although this method is objective, the rough numbers are ill-suited to handle quantitative data. The paper [6] used the Simple-normalization, Entropy-based TOPSIS, and K-means methods to improve the energy performance evaluation and ranking strategy for office buildings. This technique requires additional criteria in most cases since it is not suitable for multi-type and multi-size buildings and is not ideal for building energy efficiency dynamic evaluation. Our approach focuses on selecting a broad set of criteria that can be used to a wide range of cases.

A MCDM examination consists of four essential parts. The Decision Makers (DM) choose all of the important factors that will be used to assess the other alternatives in the Underlying Stage. An ID of this kind can be obtained by looking at the writing, based on the information on the DMs, or by asking assistance from skilled people. DMs should devote appropriate time to this step since failing to meet any important criterion may result in a futile probe.

The Subsequent Stage, decision-makers should accumulate data about every other option or a nearby score for every rule characterized in the primary stage to make the decision network. Consider a MCDM issue where the arrangement of options viable is indicated by the letters computer based intelligence = $\{a_1, a_2, . . . , a_m\}$ and the arrangement of assessment standards is addressed by the letters c_j = = $\{c_1, c_2, . . . , c_n\}$. The underneath referenced grid structure can subsequently be utilized to address the choice framework's general structure, where x_{mn} represents the choice m's score according to standards n.

Alternatives/Criteria	c_1	c_2	…	c_n
a_1	x_{11}	x_{12}	x_{13}	x_{1n}
a_2	x_{21}	x_{22}	x_{23}	x_{2n}
.	.	.	.	.
.	.	.	.	.
a_m	x_{m1}	x_{m2}	x_{m3}	x_{mn}

The Last Stage includes ascertaining every basis' weight. It is critical to take note of that assessing every one of the variables similarly isn't prudent in light of the fact that, by and by, they might have fluctuating levels of importance in a dynamic cycle. These rules loads and the neighborhood scores related with every option are consolidated into a worldwide score in the last stage. The decisions can then be positioned from most to least preferred in light of these general scores.

This article is arranged as follows: Section II covers the related work. Section III delves into problem statement and objectives of O-TOPSIS. Results and discussion is given in Section IV. Finally, the conclusion and Future directions for this research are discussed in Section V.

II. Related Work

The research map includes the following steps

Step # 1 : Systematic Literature Review

Step # 2 : Identifying Index System of Criteria

Step # 3 : Designing CRITIC - O-TOPSIS hybrid Model for decision making

Step # 4 : Ranking Alternatives

A. *Systematic Literature Review*

A systematic Literature Review was conducted to understand the implementation of TOPSIS with respect to various specializations. Also, to identify the index system of criteria for service composition in Cloud Manufacturing. This paper evaluates the different perceptions involved to find answer to the research question

Research Question: Determining the ranking to the alternatives using O-TOPSIS

The following steps followed after formulation of research question.

1. **Locating Articles** : We used Scopus Database
2. **Inclusion Criteria** :
   A. Papers that worked with TOPSIS in Cloud Manufacturing and in also areas
   B. Peer reviewed journal, reviews, and international conferences
   C. Paper title
3. **Search Strings**:
   A. Cloud Manufacturing
   B. TOPSIS
4. **Exclusion Criteria**:
   A. Papers in languages other than "English"
   B. Initial selection after reading the paper title- final selection after reading the paper abstract/ full text
5. **Analysis**
6. **Findings**

B. *Identifying Index System of Criteria*

O-TOPSIS implemented on seven criteria and in all 22 criteria including sub-criteria. These are mentioned in Table # 2

C. *Desinging Critic - O-Topsis Hybrid Model for Decision Making*

CRITIC method used to find Objective Weightgs and there by using them to implement O-TOPSIS

D. *Ranking Alternatives*

Finally ranking the alternatives

III. Proposed Approach

Extended TOPSIS [7] is used to determine sustainable supplier using. Triangle fuzzy numbers, which are used to express the linguistic data obtained from industry experts, are used to gauge the degree of ambiguity that the experts have while assessing Parameter Influencing Testing (PITs) with respect to the selection criteria. In addition, the fuzzy set is included into the AHP in order to calculate the selection criterion weights. Lastly, a fuzzy TOPSIS is used to PIT ranking [8], Geometric Mean method is used in this work. The Decision System [9] applied to large food firm for validation. The technique rated Cloud and Internet of Things (IoT) as most important 4.0 industry technologies. The developed Green low-carbon port (GLCP) evaluation index system [10] uses the FFIWAD-TOPSIS technique, applied to five major Chinese ports.

The proposed approach [11] might be applied to other economic sectors that are considered networks, such as energy or communications transmission lines, passenger and freight rail systems, and so on. "Cloud-based customization environment" and "migrating legacy system to CMfg services" were the most and least chosen CMfg applications, respectively, based on the trial results in the research paper [12]. The results [13] show that when sensor data is fused in the input vector, the NN models perform better. Validation trials confirmed the TOPSIS optimum parameters, which proved to be correct. Novel concepts have been developed, including positive and negative risks, tolerable positive and negative risks, and the risk-based TOPSIS technique for multi-period preventive maintenance scheduling [14].

To further explain and validate the created model, a case study, sensitivity analysis on two parameters, a normalization procedure, and multiple comparisons are carried out in the paper [15]. The contribution of the paper [16] is highlighting the benefits and drawbacks of various cloud services selection methodologies and their future directions, providing a taxonomy based on an extensive literature review, focusing on cutting-edge approaches to cloud services selection, and identifying nine critical challenges in cloud services selection that require additional research. The case study in [17] looks at the risk assessment of failure modes in a steam valve system to show how beneficial the recommended method is.

A. Service Composition in Cloud Manufacturing

All items, characteristics, and resources that depict a product's states, information, and mode of operation are regarded as services in the cloud manufacturing environment. These services, whose objective is to carry out actions as responses to requests between service customers and providers, can be specified, published, identified, and called through a network. Services could be delivered using cloud-based technologies and on a single server or several servers. Such services may find it more challenging to carry out the required actions when operating alone. As a result, service composition—a combination of already offered and available services from various businesses—can carry out both straightforward and difficult tasks.

B. Critic Calculation of Criteria Weights

The main steps in this procedure are

Step # 1 – Normalizing the Decision Matrix

The scores of different criteria are incommensurable as they are expressed in different measurement units or scales. Normalization is a process of transforming the scores into standard scales, which range between 0 and 1. In the proposed method, as a first step, we use the following Eq. (1) for normalizing the scores available in the decision matrix.

$$\bar{x}_{ij} = \frac{x_j - x_j^{worst}}{x_j^{best} - x_j^{worst}} \tag{1}$$

where, $\bar{x}_{ij}$ is the normalized score of alternative i with respect to criterion j, x_{ij} is the actual score of alternative i with respect to criterion j, x_j^{best} is the best score of criterion j, and x_j^{worst} is the worst score of criterion j.

Step # 2 - Calculate standard deviation, σj for each criterion.

Step # 3 - Determine the symmetric matrix of n x n with element rjk, which is the linear correlation coefficient between the vectors xj and xk.

Step # 4 - Calculate the measure of the conflict created by criterion j with respect to the decision situation defined by the rest of the criteria by using the following formula,

$$\sum_{k=1}^{m}(1 - r_{jk}) \tag{2}$$

Step # 5 - Determine the quantity of the information, Cj, in relation to each criterion by using the following,

$$C_j = \sigma_j * \sum_{k=1}^{m}(1 - r_{jk}) \tag{3}$$

Step # 6 - Determine the objective weights, Woj, by using the following

$$W_{oj} = \frac{C_j}{\sum_{k=1}^{m} C_j} \tag{4}$$

Step # 7 - Compute the integrated weights by combining the subjective and objective weights

$$Wj = \frac{W_{sj} * W_{oj}}{\sum_{t=1}^{n} W_{st} * W_{ot}} \tag{5}$$

Where, Wj represents the comprehensive weight of each criterion, Wsj represents the subjective weight, and Woj represents the objective weight

C. O-TOPSIS

The O-TOPSIS method is a multi-criteria decision-making method that ranks the available alternatives based on the closeness of alternatives to the ideal scenario considering the objective weights into account. The ideal scenario is a hypothetical ideal and best alternative. The specific steps for O-TOPSIS are:

Step # 1 – Establish the Initial Decision Matrix, A

The original data for the alternative criteria are subjected to vector standardization processing to obtain the initial decision matrix A with $m \times n$ as follows

$$A = (a_{ij})_{mxn} = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix} \tag{6}$$

$\forall$ i = 1, 2, 3, …..m & j = 1, 2, 3, …..n

For the unification and facilitating the calculations, the low-optimal criteria must be standardized into high optimal criteria.

Step # 2 – Constructing the Normalized Decision Matrix, B

In the normalized matrix, each element in B, bij is obtained using the following equation,

$$b_{ij} = \frac{a_{ij}}{\sqrt{\sum a_{ij}^2}} \tag{7}$$

After normalization, the decision matrix is,

$$B = (b_{ij})_{mxn} = \begin{pmatrix} b_{11} & \cdots & b_{1n} \\ \vdots & \ddots & \vdots \\ b_{m1} & \cdots & b_{mn} \end{pmatrix} \tag{8}$$

$\forall$ i = 1, 2, 3, …..m & j = 1, 2, 3, …..n

Step # 3: Construct a weighted normalized Decision Matrix , C

The weight of the normalized decision matrix C is obtained by multiplying the values of the index weights determined using the BWM by the values of each column of the corresponding normalized decision matrix. i.e.

$$C = (c_{ij})_{mxn} = \begin{pmatrix} c_{11} & \cdots & c_{1n} \\ \vdots & \ddots & \vdots \\ c_{m1} & \cdots & c_{mn} \end{pmatrix} \tag{9}$$

where, $c_{ij} = w_j * b_{ij}$, i = 1, 2, 3, …..m & j = 1, 2, 3, …..n

Step # 4: Calculate the positive and negative ideal solution

The maximum and minimum values in each column of matric C are selected. All the maximum values are elements of positive ideal set C+ and all minimum values are elements of negative ideal set C-

$$\begin{cases} \{C^+ = (c_j^+) = \{\max_i c_{ij} \mid j = 1,2,3,\dots,n\} \\ \{C^- = (c_j^-) = \{\min_i c_{ij} \mid j = 1,2,3,\dots,n\} \end{cases} \quad (10)$$

Step # 5: Calculate the Euclidean Distance

The Euclidean Distance is calculated from each alternative to the positive and negative ideal solutions using the following equations,

$$\begin{cases} D_i^+ = \sqrt{\sum_{j=1}^{n}(c_{ij} - c_j^+)^2} \\ D_i^- = \sqrt{\sum_{j=1}^{n}(c_{ij} - c_j^-)^2} \end{cases} \quad (11)$$

where,

D_i^+ represents the distance from alternative i to the positive ideal solution.

D_i^- represents the distance from alternative i to the negative ideal solution.

Step # 6: Calculate the Relative Ideal Solution

The relative ideal solution is the value closest to the positive ideal solution and farthest from the negative ideal solution and is calculated using the equation,

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (12)$$

where, CC_i represents the relative ideal solution for the ith alternative.

Step # 7: Rank the Alternatives

The alternatives are ranked based on the CC_i values, with the alternative having a maximum or minimum being the optimal solution.

1) Problem statement: Implementation of Multi-Criteria Decision Making (MCDM) method, the data collected and the techniques chosen for decision plays a major role.

a) Preparing the index system of criteria of service composition in Cloud Manufacturing.

b) Calculation of Objective Weights using appropriate method

c) Selecting the relevant method for ranking

d) Assigning of Ranking to the Alternatives

2) Objectives: For rating options, criteria, and sub-criteria, this article provides a hybrid multi-criteria decision technique.

a) A detailed analysis of the MCDM methods to rank the alternatives using objective weights.

b) A detailed analysis of service composition in Cloud Manufacturing

c) The objective weights of the criterion are calculated using CRITIC method.

d) To rank the various options, the Objective Weight -Technique for Order Preference by Similarity to Ideal Solution (O-TOPSIS) is used.

e) The results were compared with the conventional TOPSIS method.

IV. Results And Discussions

The initial criteria data were processed using vector standardization and the low-optimal criteria were converted to high-optimal criteria. Eq. (1) is used to obtain normalized decision matrix (it is represented in 22X5 Table, where 22 represents total criteria number and 5 represents the available alternatives). Table I represents the determined Objective Values.

A. Objective Weights using Critic

TABLE I. OBJECTIVE WEIGHTS USING CRITIC

Criteria	OW (O_{ij})
C11	0.05163
C12	0.04178
C13	0.00578
C14	0.04300
C21	0.05410
C22	0.04062
C23	0.04639
C31	0.04441
C32	0.04548
C33	0.04600
C41	0.05067
C42	0.04560
C43	0.05742
C51	0.16355
C52	0.13352
C53	0.29434
C61	0.24124
C62	0.01817
C63	0.04737
C71	0.05025
C72	0.06137
C73	0.00725

B. O-TOPSIS Implementation

The initial criteria data were processed using vector standardization and the low-optimal criteria were converted to high-optimal criteria. Eq. (7) is used to obtain normalized decision matrix (it is represented in 22X5 Table, where 22 represents total criteria number and five represents the available alternatives). Table II represents the normalized matrix values.

TABLE II. NORMALIZED DECISION VALUES -TOPSIS

	A_1	A_2	A_3	A_4	A_5
C11	6.988968	6.630559	7.317509	6.302018	6.242283
C12	5.309819	5.752304	4.505301	4.344397	4.947786
C13	1.562267	1.692456	1.432078	1.1717	1.822645
C14	4.088311	4.507625	4.140725	2.935198	3.406926
C21	1.299038	1.154701	1.732051	1.876388	0.866025
C22	1.61808	1.75292	1.21356	1.3484	1.48324
C23	1.587713	1.299038	1.154701	1.010363	1.876388
C31	1.632993	1.360828	1.360828	1.088662	1.905159
C32	1.224745	1.49691	1.49691	1.632993	1.49691
C33	1.16692	1.312785	1.312785	1.312785	1.75038
C41	2.539167	2.75681	3.119548	3.264643	2.103881
C42	3.550993	4.133992	4.557991	3.126994	3.497993
C43	2.801578	2.179005	2.863835	4.046723	4.171238
C51	1.714286	1	1.285714	1.428571	1.571429
C52	1.272792	1.697056	1.555635	1.414214	1.131371
C53	1.40028	1.820364	1.40028	1.260252	1.260252
C61	2.320168	2.223494	1.933473	1.836799	2.030147
C62	0.742781	1.114172	0.371391	1.485563	1.671258
C63	0.96225	1.154701	1.539601	0.57735	0.96225
C71	1.3484	1.48324	1.21356	1.88776	1.48324
C72	1.648327	1.510966	1.236245	1.648327	1.236245
C73	1.312785	1.45865	1.16692	1.75038	1.16692

The subjective weights calculated from BWM are used to convert the normalized decision matrix (as in Table II) by using Eq. (9). It is represented in Table III.

TABLE III. WEIGHTED NORMALIZED DECISION VALUES -TOPSIS

	A_1	A_2	A_3	A_4	A_5
C11	0.360840	0.342336	0.377803	0.325373	0.322289
C12	0.221844	0.240331	0.188231	0.181509	0.206718
C13	0.009030	0.009782	0.008277	0.006772	0.010535
C14	0.175797	0.193828	0.178051	0.126214	0.146498
C21	0.070278	0.062469	0.093704	0.101513	0.046852
C22	0.065726	0.071204	0.049295	0.054772	0.060249
C23	0.073654	0.060262	0.053567	0.046871	0.087046
C31	0.072521	0.060434	0.060434	0.048347	0.084608
C32	0.055701	0.068079	0.068079	0.074269	0.068079
C33	0.053678	0.060388	0.060388	0.060388	0.080517
C41	0.128660	0.139688	0.158067	0.165419	0.106604
C42	0.161925	0.188510	0.207844	0.142591	0.159508
C43	0.160867	0.125118	0.164441	0.232363	0.239512
C51	0.280371	0.163550	0.210279	0.233643	0.257007
C52	0.169943	0.226591	0.207708	0.188826	0.151061
C53	0.412158	0.535806	0.412158	0.370943	0.370943
C61	0.559717	0.536396	0.466431	0.443109	0.489753
C62	0.013496	0.020245	0.006748	0.026993	0.030367
C63	0.045582	0.054698	0.072931	0.027349	0.045582
C71	0.067757	0.074533	0.060981	0.094860	0.074533
C72	0.101158	0.092728	0.075868	0.101158	0.075868
C73	0.009518	0.010575	0.008460	0.012690	0.008460

Using equation (10), we determine,

The positive ideal set *(C^+)* and the negative ideal set *(C^-) represented* in Table IV.

TABLE IV. C^+ AND C^- VALUES -TOPSIS

	C^+	C^-
C11	0.322289	0.377803
C12	0.181509	0.240331
C13	0.006772	0.010535
C14	0.126214	0.193828
C21	0.046852	0.101513
C22	0.049295	0.071204
C23	0.046871	0.087046
C31	0.048347	0.084608
C32	0.055701	0.074269
C33	0.053678	0.080517
C41	0.106604	0.165419
C42	0.142591	0.207844
C43	0.125118	0.239512
C51	0.16355	0.280371
C52	0.151061	0.226591
C53	0.370943	0.535806
C61	0.443109	0.559717
C62	0.006748	0.030367
C63	0.027349	0.072931
C71	0.060981	0.09486
C72	0.075868	0.101158
C73	0.00846	0.01269

We determine D^+ and D^- values and then finally calculate the ranking of all alternatives and these results are shown in Table V.

TABLE V. THE RANKING OF ALTERNATIVES -TOPSIS

Alternative	D^+	D^-	CC_i	Ranking
A_1	0.200499	0.182409	0.476377	4
A_2	0.236396	0.183752	0.437351	5
A_3	0.162992	0.207296	0.559823	3
A_4	0.164110	0.255312	0.608724	1
A_5	0.174182	0.235665	0.575006	2

C. *TOPSIS vs. O-TOPSIS*

From the Table VI, we can observe that the ranking using Objective Weights and Subjective weights is not similar. This work can be extended using comprehensive weights to rank the alternatives in the best possible way. The comprehensive weights can be calculated using both subjective and objective weights.

TABLE VI. THE RANKING OF ALTERNATIVES - TOPSIS VS O-TOPSIS

Alternative	TOPSIS		O-TOPSIS	
	CC_i	Ranking	CC_i	Ranking
A_1	0.599674	2	0.476377	4
A_2	0.499557	3	0.437351	5
A_3	0.642782	1	0.559823	3
A_4	0.449796	4	0.608724	1
A_5	0.355450	5	0.575006	2

V. CONCLUSIONS AND FUTURE DIRECTIONS

The prime purpose of this study was to define the current or future usage of Industry 4.0 technologies (Cloud Computing, IoT etc) to improve industrial manufacturing through a thorough review. It also established critical benchmarks for assessing the specific implications of various technologies. We examined forty-five papers published between 2019 and 2023. Later, 17 papers from the Scopus database were considered. Throughout the examination, information from each publication was compiled into a large database that would be used for further research. A decision-making system will need to be constructed in the future to select the best cloud manufacturing technology within a specific firm domain.

Finally, utilising Objective Weights, this study includes a TOPSIS-based procedure for ranking and quantifying the application of the criteria using objective weights determined using CRITIC method. This technique was quite helpful in finding the most important technology.

A corporation employing a cloud manufacturing platform can use a valid selection model to pick the best cloud service provider (alternative) to improve the quality of its production and its capacity for sustained development. The following elements were considered in the model's implementation.

1) According to the CRITIC approach results, Ease of Opting has the most weight and Ease of Implementation has the least weight.

2) TOPSIS method rates options in the following order: A3>A1>A2>A4>A5.

3) The objective weights determined by using CRITIC method contribute to O-TOPSIS to obtain the desired ranking of the all the alternatives. O-TOPSIS method ranks alternatives in the following order: A4>A5>A3>A1>A2.

4) Quantitative data, including cost, is combined with linguistic assessment information when assessing cloud service providers. Moreover, DMs believe that they can communicate their preferences more clearly when they use a probabilistic word set. Consequently, the proposed method not only retains the correctness of assessment data but also effectively manages the ambiguity and uncertainty of heterogeneous information.

5) As the objective weights are more practical than the subjective weights, the result is more accurate.

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